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Comparative Advantage and Unemployment

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Abstract

We model unemployment allowing workers to differ by comparative advantage in market work. Workers with comparative advantage are identified by who works more hours when employed. This enables us to test the model by grouping workers based on their long-term wages and hours from panel data. The model captures the greater cyclicality of employment for workers with low comparative advantage. But the model fails to explain the magnitude of countercyclical separations for high-wage workers or the magnitude of procyclical findings for high-hours workers. As a result, it only captures the cyclicality of the extensive, employment margin for low-wage, low-hours workers.

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1. Introduction

Are cyclical fluctuations consistent with the Diamond-Mortensen-Pissarides (DMP) model of unemployment? Shimer (2005), Hall (2005a), Costain and Reiter (2003), and Gertler and Trigari (2009) all argue that search and matching models with flexible wages cannot generate the magnitude of cyclical fluctuations in unemployment. By contrast, Hagedorn and Manovskii (2008) rationalize this same cyclical volatility. Hagedorn and Manovskii differ in that they allow for little rents from employment: Workers receive a flow output from unemployment, reflecting the values of insurance, leisure and home production, that is the equivalent of about 95% of their earnings when employed, whereas in Shimer and Gertler and Trigari it is 40%, and in Hall and Costain and Reiter about 70%. As discussed by Costain and Reiter, Mortensen and Nagypal (2007), and others, if working yields a low flow of rents, then small shocks to the value of employment translate into large percentage shocks to the rents from employment that can yield large fluctuations in vacancies and unemployment. Thus establishing the rents from employment is key to judging how well the DMP model captures cyclical fluctuations. These papers each treat workers as homogeneous–for example, Shimer assumes a 40% replacement rate for all workers. But given workers differ markedly in both their hours and earnings when working, we expect them to differ markedly in their rents from employment. Shimer's calibration of high employment rents presumably makes sense for workers with high hours and earnings, those with high comparative advantage in market work, whereas the Hagedorn and Manovskii calibration may well apply for those workers with lower hours and earnings. The question is whether there are enough workers that display low employment rents, with enough impact on aggregate labor statistics, to generate realistic business cycle fluctuations under flexible wages.

We model unemployment, with endogenous job separations and vacancies, recognizing that workers differ in their comparative advantage in market work. To capture the level and dispersion in employment rents across workers we let workers differ in market human capital and in the value of their non-market time. We introduce enough dispersion in workers' market human capital to capture the differences we see in the data in workers' long-term wage rates. Similarly, we introduce enough dispersion in workers' values of non-market time to capture the differences we see in their long-term hours worked conditional on being employed. To achieve this latter mapping to data, we introduce an intensive margin for labor supply. Workers with a high value of market human capital to non-market predictably work more hours. This identifies these workers as those with high comparative advantage in the workforce–that is, high rents from employment.[1] Rates of separation and job finding are closely related to this comparative advantage. As in Mortensen and Pissarides (1994), we allow for shocks to the quality of employer/employee matches. A negative shock to match quality can generate an endogenous separation to unemployment. Our model predicts much higher separation rates for workers with low comparative advantage in the market. The model also predicts lower rents for employers matched to workers with low comparative advantage. For this reason, it predicts lower rates of vacancy posting and greater unemployment durations for these workers.

The paper proceeds as follows. We present the model of hours worked, separations, and vacancy creation in Section 2. In Section 3 we calibrate the model to the dispersion in wage rates and hours worked for employed men observed in panel data from twenty years of the Survey of Income and Program Participation (SIPP). More exactly, we allow for four distinct groups of workers based on workers' long-term wage rates and hours worked: (1) those with high wages and hours–ones with strong market comparative advantage, (2) those with low wages and low hours–ones with a comparative disadvantage in the market, (3) those with high wages, but low hours, and (4) those with low wages, but high hours. We let the data (SIPP) dictate the size of each group. Although the model is calibrated parsimoniously, it reasonably matches unemployment rates across the groups. In particular, it predicts that workers with below average wages and hours will exhibit nearly five times the unemployment rate of workers with above average wages and hours. This is close to the ratio of four we see in the SIPP data. The model predicts, consistent with the data, separation and unemployment rates for the remaining groups, those with low-wage and high-hours or high-wage and low-hours, that are intermediate to these extreme groups.

In Section 4 we examine the model's cyclical predictions for our four labor-market groups, comparing these to patterns observed across workers in the SIPP data. We focus on whether the model mimics the relative cyclicality of employment across the four groups and whether it can capture the high cyclicality of employment relative to the intensive hours margin. The model predicts, consistent with the data, that workers with low wages and low hours will exhibit much more cyclical employment. In particular, it predicts a big shift in separations during recessions toward low-hours workers, which we do see in the SIPP. More generally, the model matches the data well for low-wage, low-hours workers. But the model fails in two important respects. It fails

[1] Our setting shares features with Rogerson and Wallenius (2008), who allow both an extensive and intensive margins in modeling the response of total labor hours to tax changes. They model those workers at the beginning or end of the working life cycle as those with low market comparative advantage.

to capture the extent of (counter)cyclicality of separations for high-wage workers. At the same time, it fails to capture the extent of cyclicality of the finding rate for high-hours workers. For these reasons, it only captures the cyclicality of employment for workers with both low wages and low hours, while failing to capture that cyclicality for workers with stronger comparative advantage in the market.

2. Model

We model unemployment determination with endogenous separations and vacancy creation, as in Mortensen and Pissarides (1994), while allowing for heterogeneity in workers' market skills and values of non-market time (differences in labor supply). We further depart by allowing for an intensive margin of labor supply, which we exploit for matching heterogeneity in labor supply from the model to what we see in the SIPP data.

2.1. Environment

There is a continuum of infinitely-lived workers. Each worker has preferences defined by

$$E_0 \sum_{t=0}^{\infty} \beta^t \left\{ c_{mt} + c_{nt} \right\} .$$

c_{mt} and c_{nt} are respectively consumption of a traded, market-produced good and a non-traded, home-produced good. We introduce consumption of the non-traded home produced goods in order to incorporate labor supply heterogeneity into the model. We follow Mortensen and Pissarides, and the rest of the literature cited above, by assuming linear utility from consumption.[2] The time discount factor is denoted by β. We assume that the market equates $(\frac{1}{1+r})$, where r is the rate of return on consumption loans, to this discount factor; so consumers are indifferent to consuming or saving their wage earnings.

Workers differ in terms of working ability in the market and productivity at home activities. We denote market ability by a. A worker's productivity at home is given by ab. So *relative* productivity at home, that is relative to market productivity, is b. A worker with a low value for b will have comparative advantage in the market (i.e., high rents to market work.) The cross-sectional distribution of workers in the economy is denoted by $\mu(a, b)$. In calibrating we

[2] A number of papers have allowed for diminishing returns to consumption in search and matching models of unemployment. (Recent examples include Bils, Chang, and Kim, 2008, Krusell, Mukuyama, and Sahin, 2008, Nakajima, 2007, and Shao and Silos, 2007.) Based on that work, we anticipate that the qualitative conclusions drawn here would survive allowing reasonable diminishing marginal returns to consumption.

consider two values for a and two values for b. In the introduction we referred to high versus low-wage workers and high versus low-hours workers. The model will map high-wage workers to high values of a and high-hours workers to low values for b. The correlation between a and b will reflect the cross-sectional distribution of wages and hours in the SIPP data.

Turning to the home activity, we relate the value of home production to time at home according to

$$c_{nt} = ab \cdot \frac{(1-h_t)^{1-\frac{1}{\gamma}} - 1}{1 - \frac{1}{\gamma}} ,$$

where h_t are market hours. We assume γ is finite, implying diminishing returns to non-market time, $1 - h_t$, for the home activity. Our specification will yield a Frisch elasticity of labor supply for market hours h_t (the intensive margin) of $\gamma(\frac{1-h_t}{h_t})$.[3]

There is also a continuum of identical agents we refer to as entrepreneurs (or firms). Entrepreneurs have the ability to create job vacancies with a cost κ per vacancy. In calibrating we allow this cost to differ by skill and hours of the employment position, making it a function $\kappa(a, b)$. Entrepreneurs maximize the discounted present value of profits

$$E_0 \sum_{t=0}^{\infty} \beta^t \pi_t \ .$$

A worker is either matched with an entrepreneur (employed) and works or unmatched (unemployed) and available for a new match. A worker, when working, earns wages w_t. Note that w_t refers to the wage payment per period of employment, not the rate per hour. (The hourly wage rate is w_t/h_t.) This wage will differ across the workers, reflecting differences in a, b, and match quality as discussed below. These earnings are used to consume market goods. We assume, however, that there are some expenditures required by being employed, e.g. for transportation or clothing, that are not valued in c_{mt}. We set these expenditures to ω per period employed. Because they constitute a smaller share of earnings for high-wage, high-hours workers, this is an added source of market comparative advantage for these workers. If unemployed, a worker

[3] We label c_n as home production, but one could alternatively view it as the value of leisure. The interpretation as home production strikes us as slightly more natural, given that we allow heterogeneity across workers in the efficacy of their non-market time. But one can certainly contemplate workers differing in how they view the payoffs to leisure activities. Burda and Hammermesh (2009) examine how the unemployed spend their time based on time-use surveys. They find that the unemployed spend most of their extra non-market time in added leisure and personal maintenance. But, by contrast, when the unemployment rate increases disproportionately in an area cyclically the reduced time in market work is offset almost entirely by added time allocated to household production.

receives an unemployment income benefit of ϕ. In calibrating we allow ϕ to differ by a worker's long-term earnings as captured by a and b.

There are two technologies in this economy–one that describes the production of output by a matched worker-entrepreneur pair and another that describes the process by which workers and entrepreneurs become matched. A matched pair produces output

$$y_t = ax_t z_t h_t,$$

where a is the worker's ability, x_t is idiosyncratic match-specific productivity (i.e., match quality), z_t is aggregate productivity, and h_t are market hours worked. Idiosyncratic match productivity and aggregate productivity evolve over time according to Markov processes, respectively $Pr[x_{t+1} < x'|x_t = x] = F(x'|x)$ and $Pr[z_{t+1} < z'|z_t = z] = D(z'|z)$.

We assume that the matching markets are segmented by worker type (a, b). These separate markets can be interpreted as search and matching that is directed by skill and by desired hours, as workers with a high value of home time will be interested in shorter hours (e.g., part-time jobs).[4] The number of new meetings between the unemployed and vacancies in each market is determined by a matching function

$$m_{it} = \eta u_{it}^{1-\alpha} v_{it}^{\alpha}.$$

v is the number of vacancies, while u is the number of unemployed workers. i indexes the market, where i reflects $a \otimes b$. The matching rate for an unemployed worker is $p(\theta_t) = m_t/u_t = \eta\theta_t^{\alpha}$, where $\theta_t = v_t/u_t$ is the vacancy-unemployment ratio, i.e. labor market "tightness". The probability that a vacant job matches with a worker is $q(\theta_t) = m_t/v_t = \eta\theta_t^{\alpha-1}$.

A matched worker-firm constitutes a bilateral monopoly. We assume the wage is set by bargaining between the worker and firm over the match surplus, as discussed just below, where match surplus reflects the value of the match relative to the summed worker's value of being unemployed and the entrepreneur's value of an unmatched vacancy (which is zero in equilibrium). There are no wage or other bargaining rigidities. Therefore, separations are efficient for the worker-firm pair, occurring if and only if match surplus falls below zero. Furthermore the choice of hours worked within the match is efficient, maximizing match value.

The timing of events is as follows. (1) At the beginning of each period matches from the

[4] Guerrieri, Shimer, and Wright (2009) characterize separating contracts in a search environment, such as here, with distinct types. Signalling high labor supply, by searching in a market that specifies employment with longer hours, will be more costly for low-labor supply workers.

previous period's search and matching are realized. Also aggregate productivity z and each match's idiosyncratic productivity x are realized. (2) Upon observing x and z, matched workers and entrepreneurs decide whether to continue as an employed match. Workers breaking up with an entrepreneur become unemployed, with the match permanently ended. (3) For matched workers, hours and wages are chosen and production takes place. Hours are chosen to maximize match surplus with the wage reflecting worker-firm bargaining. Concurrent with production, unemployed workers and vacancies engage in the search/matching process.

2.2. Value functions and choices for hours, separations, and wages

We turn next to describing the value functions for employed and unemployed workers, as well as the determination of hours and wages within matches. The assumptions above of linear utility in consumption, linear production in labor, and a constant returns to scale matching function imply that choices for vacancies, separations, hours, and wages in the market for one labor group (e.g., the high market-skill, high labor-supply market) are independent of choices and outcomes in the other labor markets. For this reason, for the balance of this section we dispense with indexing variables with the index i for market type. We also dispense with time subscripts: variables are understood to refer to time period t, unless marked with a prime ($\prime$) denoting period $t+1$.

First consider the choice of hours. We assume that firms and workers bargain efficiently, maximizing the value of match surplus. This requires choosing hours to equate the marginal product of an hour in the market to its marginal benefit at home: $axz = ab(1-h)^{-1/\gamma}$. So optimal hours at the intensive margin for a worker are

$$h^* = 1 - (\frac{b}{xz})^{\gamma}\,.$$

Turning to the value functions, a worker's valuation of being employed is

$$W(x,z) = (w(x,z) - \omega) + \frac{ab}{1-\frac{1}{\gamma}}((\frac{b}{xz})^{\gamma-1} - 1) + \beta E\left[\max\{W(x',z'),U(z')\}|\, x,z\right]\,.$$

Note that the expenditures necessitated by employment, ω, are netted from the wage payment. The value of home production reflects the optimal choice of market hours h^*. The maximization problem implicit in $W(x,z)$ is to choose a cut-off value, x^*, such that the match persists only if match quality x exceeds that value.

The value of being unemployed is

$$U(z) = \phi(a,b) + \beta(1-p(\theta))E\left[U(z')|\, z\right] + \beta p(\theta)E\left[W(\bar{x},z')|\, z\right] \ ,$$

Home production for the unemployed is normalized to zero. Recall that $p(\theta)$ is the probability that an unemployed worker matches with a vacancy. We assume that new matches begin with a match quality equal to the mean, $\bar{x}$, for the distribution of x. For the parameter values we consider, this ensures that workers will in fact accept new matches.[5]

For an entrepreneur the value of a matched job is:

$$J(x,z) = axz(1-(\frac{b}{xz})^{\gamma}) - w(x,z) + \beta E\left[\max\{J(x',z'),V(z')\}|\, x,z\right] \ .$$

The value for current production reflects the optimal choice for hours. For a Frisch elasticity γ strictly greater than zero, hours are procyclical. In turn, this adds to the procyclicality of J. The value of a matched job J reflects the option value of being able to end the match for $t+1$ if match quality falls below x^*.

The value of a vacancy is:

$$V(z) = -\kappa(a,b) + \beta q(\theta)E\left[J(\bar{x},z')|\, z\right] + \beta(1-q(\theta))E\left[V(z')|\, z\right] \ ,$$

where recall that κ is the vacancy posting cost and $q(\theta)$ is the probability that a vacancy is filled. With free-entry in creating vacancies, in equilibrium $V(z)$ will equal zero.

We assume the wage payment is set by Nash bargaining between the worker and firm over the match surplus according to:

$$\underset{w}{\operatorname{argmax}} \ \Big(W(x,z) - U(z)\Big)^{\chi}\Big(J(x,z) - V(z)\Big)^{1-\chi},$$

where $0 \leq \chi \leq 1$ reflects worker share of match surplus. This wage payment is predictably increasing in ability a, especially since a increases the value of non-market as well as market

[5] Alternatively, we could allow that new matches draw from a distribution of match qualities. The creation of new employment matches would then mimic our endogenous model of the separation decision–new employment matches would occur conditional on both matching and drawing a match quality x above a critical value x^*. Our model predicts less creation of vacancies for workers with low comparative advantage in the market, resulting in these workers having a lower finding rate. Our model also predicts that these workers will exhibit a higher value for critical match quality x^*. Therefore, extending the model to allow for endogenous take up of new matches would reduce the finding rate further for workers with low comparative advantage. We do not pursue this, largely because the model already predicts a lower finding rate for workers with low hours than we observe in the SIPP data.

time. For $\chi < 1$, the wage will also be increasing in relative home productivity b. For $\chi > 0$, the wage payment is increasing in match productivity x and aggregate productivity z. The impacts of x and z on the wage payment reflect not only their direct roles in productivity, but also their positive impacts on hours worked.

3. Fitting the Model to Data

We first describe the SIPP data, then use it to construct statistics on employment and turnover for four distinct groups based on workers' long-run hourly wages and hours worked when employed. We next calibrate the model to feature four groups that align with the wage and hours dispersion we see in the SIPP. Finally, we examine how well the model matches the data in terms of rates of employment and turnover across the four groups.

3.1. Our SIPP sample

The SIPP is a longitudinal survey of households designed to be representative of the U.S. population.[6] It consists of a series of overlapping longitudinal panels. Each panel is about three years in duration. Each panel is large, containing samples of about 20,000 households. Households are interviewed every four months. At each interview, information on work experience (employers, hours, earnings) are collected for the three preceding as well as most recent month. The first survey panel, the 1984 panel, was initiated in October 1983. Each year through 1993 a new panel was begun. New, slightly longer, panels were initiated in 1996 and again in 2001. In our analysis we pool the 12 panels, with the exception of the panel for 1989, which is very short in duration. Given the timing of panels, the number of households in our pooled sample will vary over time, with a gap between surveys at the beginning of 1996 and during 2000.

For our purposes the SIPP has some distinct advantages. Compared to the CPS, its panel structure allows us to compare workers by long-term wages or hours. It also provides information on employer turnover. Unlike the CPS, respondents who change household addresses are followed.[7] The SIPP has both a larger and more representative sample than the PSID or NLS panels. Individuals are interviewed every four months, rather than annually, so respondents' recall of hours, earnings, and employment turnover since the prior interview should be considerably better.

[6] We do employ SIPP sampling weights, however, in constructing all reported statistics. These weights are designed to maintain a representative sample despite sample attrition.

[7] Fujita, Nekarda, and Ramey (2007) present detailed results on the cyclicality of separation and finding rates for all workers in the SIPP, comparing these to patterns in the CPS.

We restrict our sample to men between the ages of 20 and 60. Individuals must not be in the armed forces, not disabled, not be attending school full-time, and must have remained in the survey for at least a year. We further restrict the analysis to those who averaged at least one month of employment per year (so at least three separate months for someone with a typical three years of interviews) and who have data on both hours worked and earnings for at least one month.[8] The pooled sample that results consists of 73,416 separate individuals, representing data on employment status for 1,925,354 monthly observations.[9]

We focus on a respondent's monthly rates for being employed in a match, separating from employment, finding employment, hours worked, and hourly wages. We define a worker as employed in a match if he reports being with a job the entire month (with no more than two weeks without pay) and reports no weeks primarily involved in search. We also classify a worker who is temporarily away from work as employed in a match provided he returns to the same employer within three months and reports no weeks of searching. In this case, weeks not actively working are reflected in the worker's measured hour worked conditional on being matched–the intensive margin.[10] We will typically refer to men not employed in a match as unemployed. We believe this best conforms to the model's definition of unemployment. But note that, unlike official unemployment statistics, this classification does not require that the unemployed worker report actively searching for employment. Our sample of men averages an employment (matched) rate of 92.9%, with 7.1% for unemployed (unmatched). Our measures for monthly job separation and finding rates follow immediately given the definition for being matched with an employer: A separation corresponds to transiting from being matched to unmatched; a job finding is a transition from unmatched to matched. These rates average, respectively, 1.5% and 18.5% monthly for our sample.

Our measure of hours worked in a month (the intensive margin) reflects variations in hours worked per week, weeks worked per month, and occurrences of temporary layoffs.[11] We first multiply hours worked per week times weeks worked per month, then take the natural log. To

[8] We treat self-employed workers as employed, rather than unemployed. We base a worker's market wage rates and hour worked only on months working for an employer (not self-employed) and only on months with usual weekly hours of at least 10.

[9] The SIPP interviews provide distinct answers on employment status and weeks worked for each of the prior four months. But for wage rates and weekly hours the data attribute the same values for each of the four months covered in an interview. Therefore, we restrict attention to the survey month observations in examining the cyclicality of hours and wage rates in Section 4.

[10] Just under one-half of one percent of our sample fall under this "temporary layoff" category. So it does not have much impact on rates of employment and unemployment.

[11] Our measured weeks worked adjusts for the number of weeks in a month. Measured hours worked per week can reflect hours worked at up to two jobs.

reflect temporary layoffs, we then add to this a term $(\Gamma/\bar{\Gamma} - 1)$, where Γ is a zero/one variable equal to one if not on temporary layoffs, and $\bar{\Gamma}$ is the mean value of Γ (0.995 for our sample). But variability in this component, temporary layoffs, contributes relatively little to the variability of our measured intensive margin either cyclically or in judging workers' relative long-term hours. We measure the wage rate by the hourly rate of pay on the main job. More than sixty percent of workers report a wage in this form. For the others we construct an hourly rate from their reported hours and earnings, based on how the hourly wage projects on these variables for those who do report an hourly wage. We deflate the wage rate by the Consumer Price Index.

3.2. Employment and turnover by long-term wages and hours in the SIPP

For each worker we first calculate their average (long-run) wage rate and average (long-run) hours worked. We then put the workers into one of four bins based on whether their long-run wage is above or below the median value and whether their long-run hours are above or below the median. To construct these we average a worker's (ln) hourly wage rates and (ln) hours worked over all months employed.[12] The median long-term wage is \$16.63 per hour in January 2009 dollars. The median long-term hours worked is 180 per month. The standard deviations equal 42% for the hourly wage and 19% for hours worked. The correlation between long-term wage and long-term hours is positive, but fairly small, at 0.15.

Statistics for the four groups, low-wage/low-hours, low-wage/high-hours, et cetera, are contained in Table 1 through 3. Table 1 reports each group's share in the sample. Reflecting the modest positive correlation between long-term wage and hours, the diagonal groups, low-wage/low-hours and high-wage/high-hours are modestly larger, each at 26.7% of the sample, than the off-diagonal groups, low-wage/high-hours and high-wage/low-hours, each at 23.3% of the sample. But it is worth noting that the off-diagonal groups still combine for nearly half (46.6%) of the sample. For this reason, it would greatly misrepresent the data to model heterogeneity in labor supply as captured only by heterogeneity in market skills.

Table 2 reports each group's mean long-term (ln) wage and mean long-term (ln) hours, both

[12] We first project the natural log of a worker's hourly wage for each month, the natural log of his hours per month conditional being actively employed, and his value for the temporary layoff variable $(\Gamma/\bar{\Gamma} - 1)$ on a full set of monthly dummies to obtain the worker's residual wage, hours, and layoff variable relative to other person's for that month. (This regression also includes a dummy variable for whether data is drawn from the earlier or later SIPP panels, as some hours and earnings variables change slightly beginning with the 1996 panel.) The residuals for these variables are then averaged across months for an individual to obtain his long-term wage and hours worked. Long-term hours worked reflects the sum of the variables for the worker's long-term hours worked conditional on being actively employed and his long-term mean for the variable capturing not on temporary layoff $(\Gamma/\bar{\Gamma} - 1)$.

expressed as its deviation from the mean for the entire sample. Overall, the high-wage workers exhibit 68% higher wages than the low-wage workers, with this differential 71% among workers with low hours and 64% among workers with high hours. High-hours workers, overall, work 25% more market hours than low-hours workers, with this differential a little larger among workers with low wages, 28%, than among low-wage workers, 22%.[13]

Table 3 reports employment and turnover rates across the four groups. We focus first on the two extreme groups along the diagonal. Low-wage/low-hours worker exhibit an employment rate of only 87.6% compared to 96.8% for those with both high wages and high hours worked, conditional on employment. This differential appears more extreme if viewed in terms of the unemployment rates, representing a rate nearly four times as large (12.4%) for the low-wage/low-hours group compared to that (3.2%) for men with high wages and hours. Given this extreme differential, it is not surprising that the low-wage/low-hours workers display both higher separation rates and lower finding rates. But this difference is much more striking for separation rates. Workers with low wages and hours show three times the separation rate as the opposite extreme group (2.4% versus 0.8%), whereas their finding rate is only lower by a factor of about 20 to 25%. Thus, most of the difference in employment rates between the two groups can be mapped back to the difference in separation rates.

Employment rates for the off-diagonal groups are intermediate to these two extremes. The employment rate for the low-wage/high-hours workers is 92.1%; for the high-wage/low-hours workers it is 95.0%. Rates of separation project much more on workers' long-term wage rates, whereas finding rates are better explained by differences in hours worked. Workers with low-wages and high-hours actually show a slightly higher finding rate (22.1%) than high-wage/high-hours workers (21.3%). But the separation rate for these workers (1.9%) is much closer to that of the low-wage/low-hours workers. Similarly, the finding rate for high-wage/low-hours workers is even lower than that for the extreme group with both low wages and hours. But their separation rate (1.0%) is much closer to that of the high-wage/high-hours extreme.

[13] Appendix tables A1 and A2 report on the distributions of schooling attainment and age for each of the four groups. The high-wage groups average about 1.5 more years of schooling than the low-wage groups, while the high-hours groups are, on average, about 2.1 years younger than those working less than the median number of hours. (Workers ages 51 to 60 are less common among low-wage workers who work high hours.) But it is clear that schooling and age differences capture only a modest part of the dispersion in wages and hours across groups. Appendix table A3 reports the fraction of workers in each group employed in cyclical industries–manufacturing, construction, and transportation. The fraction in cyclical industries is fairly similar across the four groups. So differences in employment cyclicality by group, reported below, should not heavily reflect differences in industry composition. The fraction in cyclical industries is modestly higher for the high-wage workers, averaging 43%, than for the low-wage, 34%. It is essentially the same for high-hours workers, 39%, and low-hours workers, 38%.

3.3. Calibrating the model

There are four types of workers in our model economy, with these types distinguished by two distinct values for market ability, a, and two distinct values for home productivity relative to market, b. All parameters except the payment for unemployment benefits and the firm vacancy posting cost will be common across these four groups. (As described below, the unemployment benefits and posting cost are assumed proportional to the workers' long-term market output.) We proceed by first calibrating these common parameters to fit data for the high-wage/high-hours group, the group that is most strongly attached to the labor market. We typically will refer to this as the southeast group, corresponding to their location in the tables. The key outcomes we target are the average rates of employment, separations, and job finding for the high-wage/high-hours group in the SIPP data. (See the southeast corner of Table 2.) After calibrating for this southeast group, we then choose values for a and b to map out the remaining three groups to be consistent with dispersion we reported in Table 1 for wage rates and hours from the SIPP data. We then ask how well the model captures rates of employment and turnover for these groups.

The two preference parameters to calibrate are the discount factor and the Frisch elasticity for the intensive labor margin. We use a monthly discount factor β of 0.9966, implying an annualized real interest rate of 4%. The Frisch elasticity, equal to $\gamma(\frac{1-h}{h})$, reflects both the parameter γ and the level of hours worked. Recall that hours worked equal $1-(\frac{b}{xz})^{\gamma}$. We first normalize market ability a for the southeast group to one. We further normalize, for all groups, the mean for the distribution of match quality, x, and steady-state aggregate productivity, z, both to one. This implies market hours for the southeast group, evaluated at mean match quality, of $1-b^{\gamma}$. Finally, we set b and γ so that market hours equal 0.5 with a Frisch labor supply elasticity of one third. This requires $\gamma=1/3$ and $b=1/8$. Kimball and Shapiro (2003) and Hall (2009) each survey estimates for the Frisch elasticity. Much of the evidence suggests a value of 0.5 or below. Hall, largely based on Pistaferri (2003), chooses a value of 0.7. As discussed below, we impose the same parameter value of 1/3 for γ across our four groups. This implies a larger Frisch elasticity for workers who work shorter hours, with the average Frisch elasticity across our groups equal to 0.44.

The key outcomes we target are the average rates of separations and job finding for the southeast group in the SIPP data. In turn, these rates depend primarily on the replacement rate while unemployed, the size of idiosyncratic shocks to matches, and the vacancy posting cost. The size of the replacement rate reflects the unemployment benefit, ϕ, the expenditure saved by not working, ω, and the extra home production when unemployed. We set the unemployment benefit ϕ equal to 0.1, which corresponds to 20% of long-terms earnings for the southeast group.[14] Shimer (2005) assumes a replacement rate of 40%; but for his calibration this rate should reflect any gains with unemployment from increased leisure or home production, whereas we have this as an explicit, separate component. We set the expenditure necessitated by work, ω, at 0.05, which represents 10% of long-run earnings.[15] The gain in home production while unemployed for the southeast group (given the values for h, b, and γ) equals 37.5% of market productivity. Combined with the unemployment benefits and expenditures required for working, this yields a steady-state replacement ratio equivalent to 67.5% of market output for the southeast group.[16] This value is considerably higher than the 40% employed by Shimer's calibration, but close to the replacement rates assumed by Costain and Reiter (2003) and by Hall (2005a). Those authors, however, employ that ratio for all workers, whereas we employ it only for high-wage/high-hours workers.

We assume shocks to match-specific productivity are highly persistent, setting their autocorrelation equal to 0.98. We then set the volatility of these shocks, σ_x, together with the vacancy posting cost, κ, in order to mimic the monthly separation and finding rates (0.77% and 21.3%) that we observe for the southeast group in the SIPP data. This is approximately achieved by $\sigma_x = 0.026$ and $\kappa = 0.30$. Given σ_x, the model generates a dispersion in match quality among employed workers of about 5%. We view this as a conservative value for dispersion in match quality–it translates to only one eighth the standard deviation in wages we observe in the SIPP data.[17] The vacancy posting cost translates into a cost per hiring of about six week's expected

[14] Hall (2005b) shows that the replacement rate has been about 15 percent in recent years. We prefer to err on the high side in calibrating the replacement rate, as a lower rate would serve to reinforce our negative conclusions for the model discussed in Section 4.

[15] Aguiar and Hurst (2009) argue, based on life-cycle spending patterns, that an important component of spending on food away from home, clothing, and transportation reflect employment variation over the lifecycle. They regress spending shares by category on separate dummy variables for employment of the husband and wife. The estimated impact of employment, given total consumption, just on these three categories support assuming that 5% or more of consumer spending is driven by employment expenses. In addition, any costs that fall on the employer that have a fixed, per worker, nature should also be folded into ω, as these costs would act in the model precisely like the expenditures in ω. One example of such costs are payroll taxes (e.g., FICA or for UI) that have a per worker component or are capped above some earnings level.

[16] This is evaluated for match quality, x, equal to its expected value of 1. Workers select into values of match quality that average higher, as bad matches lead to separations. For our calibration, this selection raises productivity and wages by about three percent. The replacement rate relative to mean actual earnings is about 65 percent for the southeast group.

[17] Woodcock (2007) allows for individual, employer, and match components in explaining dispersion in earnings for a large sample of matched employer-employee records across 37 states. He finds a standard deviation of the match component in earnings that is more than one-third the standard deviation in overall earnings. Increasing dispersion in match quality would reinforce our primary conclusions that the DMP model fails to generate

output. For the Cobb-Douglas matching technology, $m(v, u) = .3\, v^{\alpha} u^{1-\alpha}$ hits the steady-state finding rate. We set both the matching power parameter α and the bargaining share for workers χ equal to 0.5. Finally, the model's separation and finding rates for the southeast group, 0.75% and 22.3%, together imply a steady-state employment rate of 96.7%.

We now turn to the parameters that vary across groups. We choose the size of the four groups to match those in the SIPP data: 27% for high-wage/high-hours and low-wage/low-hours, and 23% for high-wage/low-hours and low-wage/high-hours. We choose the earnings ability for low-wage groups ($a = 0.5$) to make the cross-sectional dispersion of log wages across our four groups in the model roughly comparable to that of long-term wages in the SIPP data. For the low-hours groups, we set relative home productivity (relative to market) equal to 0.25 in order to generate a cross-sectional dispersion in log hours that mimics the data. Summarizing, the ability parameters are $\{(a, b) = (1, 0.125), (1, 0.25), (0.5, 0.125), (0.5, 0.25)\}$, respectively, for workers with high-wage/high-hours, high-wage/low-hours, low-wage/high-hours, and low-wage/low-hours.

We allow two parameters, the unemployment benefit (ϕ) and vacancy posting cost (κ) to vary across groups. We make each proportional to that group's long-term earnings. Scaling ϕ to earnings gets at the practice that unemployment insurance is proportioned to past earnings.[18] The replacement ratios for these four groups, which define the rents to employment relative to market productivity, are respectively 67.5%, 77.5%, 84.8%, and 98.4%. We view this as a generous calibration for these replacements rates–the average rate across the groups is 82% and the low-wage, low-hours workers (27% of all workers) are assumed to have very low rents from market employment. We scale the posting cost to the group's long-term earnings to reflect data (e.g. head-hunter's fees) that typically express the employer's costs for matching in terms of compensation at the job. The values implied for κ across the four groups are respectively 0.30, 0.22, 0.15, and 0.11.[19]

cyclicality in the extensive margin. By increasing match rents, separations become less responsive to aggregate cyclical shocks, yielding less cyclical employment.

[18] Anderson and Meyer report the level of unemployment benefits by wage decile based on the 1993 panel of the SIPP data. Benefits, as a share of earnings, are much lower at higher wages. But unemployment is also greatly skewed toward lower wage workers. If the breakdowns in benefits by wage from Anderson and Meyer are viewed together with a breakdown in unemployment by wage, this suggests an elasticity of unemployment benefits with respect to wage that is close to one.

[19] More exactly, ϕ and κ are scaled to the group's steady-state product $(a \times h(a, b))$ evaluated at match quality at its mean value. Long-term earnings are slightly higher, reflecting selection on match quality.

3.4. How well does the model fit the cross-section?

Table 4 presents the model's steady-state wages and hours worked for each of the four labor groups. Each high-wage group, for low or high hours, displays a wage that is about 68% greater than the low-wage group with comparable hours. The model generates slightly lower, 1 to 2%, lower wages for high-hours workers. This reflects both that high-hours workers exhibit a lower reservation match quality for staying employed and bargain for a slightly lower wage, given productivity. The difference in wages across groups in Table 4 matches very closely the average differential by group observed in the SIPP data (Table 2). But wage dispersion in the SIPP, with standard deviation 0.42, is greater than that for our model economy, 0.34, as it reflects dispersion within as well as between the four groups. Turning to hours, each high-hours group for the model displays hours worked of about 27% higher than that for the low-hours group with comparable wage rates. This is close to what we see in the SIPP data, where those differentials are about 25%. The model generates an overall standard deviation in hours worked of 15%, lower than that of 19% for the SIPP data. The cross-sectional correlation of log hours and log wages in our model is 0.05, somewhat lower than that in the SIPP (0.15). The higher standard deviations of wages and hours, and their slightly higher correlation, in the SIPP data reflects its heterogeneity of wages and hours within each of the four groups. This is missing for the model simulated data, except for the effects of small differences in match quality. (For this reason, in examining the cyclical behavior of hours for each group in Section 4, we correct for any cyclical compositional effects within each group.)

Table 5 presents the employment, separation, and finding rates for the model's steady state by group. We focus first on the two extreme groups: low-wages/low-hours workers (the northwest cell in the tables) and high-wage/high-hours (the southeast). The employment, separation, and finding rates for the southeast group all correspond closely, by construction, to those observed in the SIPP data (Table 3). The model yields an employment rate of 83.8% for the northwest group. So the unemployment rate for the northwest group, 16.2%, is nearly five times that for the southeast group. This is close to, but a bit more extreme than, what we see in the SIPP, which shows an unemployment rate for the northwest group of 12.4%. For the northwest group the model exhibits separation and finding rates that are both lower, at 1.9% and 8.8%, than observed in the SIPP, 2.4% and 16.8%. Like the data, the model predicts intermediate employment rates, intermediate to the southeast and northwest groups, for the off-diagonal groups with, respectively, high wages and low hours (northeast group) and low wages and high hours (southwest group). But the model predicts higher unemployment for the high-wage/low-hours group

(6.1%) than for the low-wage/high-hours (4.5%), whereas for the data this is reversed (5.0% for the northeast group and 7.9% for the southwest). Most notably, the model under-predicts the separation rate for the low-wage/high-hours group, predicting a rate of 0.9% compared to 1.9% in the SIPP data. More generally, that is with the exception of understating the separation rate for low-wage workers, the model does reasonably well.

The differences in separation and finding rates across the four groups are directly related to the rents to employment. These rents are represented by the difference between the match quality, x, that a worker has in employment versus the critical match quality, x^*, at which the match would be dissolved–a match with $x = x^*$ would have zero rents. In Figure 1 we present the distributions of $x - x^*$ separately for each of the groups. The northwest group (lower wage and hours) is distinct from the other three. In particular, the fraction with $x - x^*$ below five percent is nearly twice as large for this group than for the other three. This explains why the model predicts a steady-state separation rate that is nearly twice as high for this northwest group than it predicts averaging over the other three groups. The distributions of $x-x^*$ are also telling for the cyclical behavior of separations and employment across the four groups, which we examine next. The larger number of workers with low values for $x - x^*$ for the northwest group predictably leads to a sharper increase in separations during a downturn for this group. Secondly, the lower average value of $x - x^*$ for the northwest group means that a decline in aggregate productivity, which increases x^*, will create a greater percentage drop in $x - x^*$, in turn causing a larger reduction in vacancy creation rates and finding rates for this group.

4. Business Cycles, Model vs. Data

We are now in position to compare the labor market business cycles produced by our calibrated model to what we observe from the SIPP data. We create business cycles for the model by hitting each group with persistent shocks to aggregate productivity z. (These shocks display an autocorrelation of 0.97, with innovation standard deviation of 0.37%.) We first compare the model and data in terms of their predictions for the relative size of cyclical fluctuations in employment across the four groups. Secondly, we examine whether the model and data conform in their predictions for the relative importance of the intensive, hours margin and the extensive, employment margin for each of the groups. Thirdly, we look in more detail at the employment response by examining the cyclicality of separation and finding rates across the four groups. Lastly, we examine the cyclical implications of aggregating our four labor groups.

4.1. Cyclicality in hours and employment

In Table 6 we compare the responses of employment for each of the four groups to aggregated employment, comparing the model predictions to the evidence from the SIPP. For both the SIPP and model series we HP filter with monthly smoothing parameter 900,000. We also remove monthly seasonals for the SIPP-based series.[20] We instrument for aggregated employment reported in the SIPP based on the U.S. unemployment rate for men and average weekly hours for workers, both reported by the BLS. (The unemployment rate is based on the Current Population Surveys, weekly hours on Current Employment Statistics.) We instrument so that measurement error in the SIPP does not influence the estimated relative importance of employment responses across groups or the relative importance of employment and hours responses.

Focusing on the extreme groups in Table 6, both the model and the data display much larger cyclical employment responses for low-wage, low-hours workers than for those workers with higher wages and hours, but for the model this contrast is more extreme. For the data, the employment response for the northwest group (low-wage/low-hours) is 1.7 times the aggregate response, whereas for the model that ratio is 3.0. For the data, the employment response for the southeast group (high-wage/high-hours) is only 0.42 times the aggregate response; but for the model it is less than half that, at 0.17. In the SIPP data the intermediate groups each display cyclical employment responses that are 0.7 times the aggregate response. For the model these responses are 0.55 for those with high wages, but low hours, and 0.34 for those with low wages, but high hours. In sum, for the model employment cyclicality is confined to a greater degree to the low-wage, low-hours workers compared to what we see in the data.

In Table 7 we compare the responses, in the data versus the model, of hours worked and employment to cyclical movements in aggregate total labor hours–i.e. hours times employment.[21] We instrument for aggregated total hours reported in the SIPP, again based on the national unemployment rate for men and national weekly hours. The model and the data match remarkably well for the low-wage, low-hours workers–both predict a greater cyclical response for the

[20] The SIPP surveys have breaks in coverage during 1996 and 2000. These breaks are exaccerbated because we restrict our employment series to months that reflect at least half of a full SIPP panel, and a panel rotates in (and out) over a four month period. This results in a time series for employment from August 1983 to September 2003, with 226 monthly observations plus 16 missing months. (We base the HP filter for a SIPP-based series on that series with interpolated values for the missing gaps.)

[21] Aggregated total hours equals the average across all workers of the sum of ln(hours) and the percentage deviation of the zero/one employment rate from its mean value. For the data, the hours statistics correct for cyclical compositional changes by long-term hours *within* each group. For each group we calculate a time-series for the mean fixed effect of employed workers for hours. The series for the fixed effect in hours is then netted from the time series for hours.

extensive margin, in fact both predict an employment response that is 2.5 times the cyclical response in the intensive margin. But for each of the other three groups the model substantially under predicts the relative cyclicality of the employment margin. For both intermediate groups the model predicts cyclical responses in the hours margin that are more than double that for employment; but in the data this ratio is nearly reversed. For the high-wage, high-hours group both the data and the model show a greater response in hours, rather than employment. But the model predicts an hours response that is nearly five times the magnitude of that for employment, whereas in the data these responses are comparable in size.

The model does not capture the cyclicality of employment for workers with comparative advantage even though the replacement rates we allow for these workers–67% for high-wage/high-hours workers and an average of 80% for the two groups off the diagonal–is fairly high. More importantly, increasing replacement rates, for example by raising the fraction of earnings replaced by unemployment insurance, is not a reasonable solution. To generate a cyclical response in employment (relative to hours) for high-wage/high-hours workers like what we see in the data requires doubling unemployment insurance, from 20 to 40% of earnings. But calibrating unemployment insurance at this level, while respecting the wage and hours differences across workers, drives the total replacement rate on average above 100% for the other three groups. In particular, the replacement rate for workers with low wages and hours goes well above 100%. As a result, the model predicts zero employment for these workers, whereas in the data their employment rate is over 80%.[22]

4.2. Cyclicality in separation and finding rates

The responses, by group, of separation and finding rates to the aggregate total labor hours are given in Table 8. We know from Table 7 that the response in employment in the data exceeds that predicted by the model for each of the groups except those with low wages and low hours. The results in Table 8 suggest whether this reflects an inability to predict the cyclicality of

[22] The model assumes Frisch elasticities for hours of one third for high-hours workers and a little over one half for workers with lower hours. One might conjecture that the model's failure to capture the relative importance of the extensive versus intensive margins could be fixed by assuming smaller Frisch elasticities. But this is problematic. Reducing the Frisch elasticity makes market and non-market work poorer substitutes, which acts to increase the gains from employment. For instance, cutting the Frisch elasticities in half reduces the effective replacement value from leisure by 18% of earnings for high-hours workers and by 23% of earnings for low-hours workers. As a result, the model will generate much smaller employment fluctuations for all groups. This is exaccerbated by the fact that, to generate realistic separations with the higher employment rents, the calibrated model requires larger match-specific shocks (larger σ_x), further insulating employment from cyclical shocks. Thus, reducing the Frisch elasticity to low values does not correct the failure of the model to predict the cyclicality of employment compared to hours.

separations or that of findings.

The results differ notably by group. For three of the groups, all but the low-wage, high-hours group, separations are more countercyclical for the data than predicted by the model, with this mismatch most striking for the two groups with higher wages. By contrast, separations in the data are acyclical for the group with low wages, but high hours. Turning to finding rates, we see that both the data and model display procyclical finding rates for all four groups. But for the most cyclical workers, those with low wages and low hours, the model predicts finding rates that are far too cyclical. For this group most of the cyclical action in the SIPP data occurs through countercyclical separations. By contrast, the model under predicts the cyclicality of the finding rate for high-hours workers, particularly those with lower wage rates.[23] To summarize, our calibrated DMP model fails to explain how much separations increase during recessions, particularly for high-wage workers, and how much the finding rates falls during recessions for high-hours workers.

4.3. Aggregate patterns

Aggregation puts a disproportionate weight on the low-wage, low-hours workers due to their much greater cyclicality. Table 9 presents statistics on cyclicality of hours versus employment, for the SIPP data and for our model economy, aggregating the workers into a single workforce. In the data cyclical fluctuations in employment are more important, contributing about 70% of fluctuations in total hours. The model's aggregated simulated data predicts that cyclical fluctuations are reflected about equally in hours (48%) and employment (52%). So the model understates the importance of the extensive margin. Aggregating does increase the importance of the employment margin for the model, compared to the simple average of its importance across each of the four groups reported in Table 8. This reflects the disproportionate weight of the low-wage, low-hours workers in aggregate fluctuations. For this group the model does generate that 70% of fluctuations occur through the extensive margin.

Table 10 presents the responses of aggregate turnover rates to total labor hours for both the data and model. For our model a 1% increase in aggregate total hours is associated with

[23] Shimer (2005) and Hall (2005a) each point to wage rigidities as a possible explanation for very procyclical finding rates. But wages are actually more procyclical for this group, those with low-wages and high hours, than for the other three. More generally, we do not draw comparisons of wage cyclicality for the model and data because it is difficult to ascertain the allocative wage if there is wage smoothing as anticipated by the implicit contracting literature. For example, we find an aggregate response of wages to total hours of 0.34 (standard error of 0.12) compared to a model prediction of 1.02. But if we restrict the sample to new hires, those hired within the past 12 months, the wage response in the SIPP data increases from 0.34 to 0.90 (with standard error of 0.32).

a decrease in the separation rate of 2.5%. The data show a modestly larger decrease of 3.0%. The cyclicality of the finding rate, again conditioning on the same 1% increase in total labor, is considerably larger for the model than data (5.3% for model compared to 3.9% for the data). This discrepancy can largely be traced to the low-wage, low-hours workers. From Table 8, the model predicts that much of cyclicality for this group occurs through the finding rate, whereas in the data cyclicality of employment is much more driven by the separation rate. This group receives disproportionate weight in determining the aggregate cyclicality of the finding rate as they make up about half of the unemployed. For this reason, the aggregated statistics show a coefficient of cyclicality for the finding rate, conditional on a change in total labor, that is well above the model's average across the four groups and well above that displayed by the data.[24]

For both the model and data, we see that separations are skewed during recessions toward workers who work fewer hours, independently of the cycle. In turn, this creates a compositional shift during recessions toward a pool of unemployed who: (a) typically work fewer hours, and (b) display lower finding rates. For the model we calculate that this compositional shift explains about one-sixth of the cyclicality of the finding rate for the aggregate economy (about one-sixth of the coefficient of 5.3). For the data there is also an important compositional shift in separations and the unemployment pool toward workers who work fewer hours independently of the cycle. But, because the finding rates differ less markedly across groups in the data, the implications for the aggregate finding rate are much smaller.[25]

[24] Shimer (2005) stresses that his calibrated DMP model generates a standard deviation for (ln)unemployment relative to that for labor productivity that is about one half, whereas in the data this ratio is about 10. We have not emphasized this statistic. Because we cannot say that the only disturbance to employment is productivity shocks, we do not want to judge the model by unemployment's volatility relative to volatility only in measured productivity. But it is useful to report these relative volatiles for our model's simulated business cycles to facilitate comparing our model to others in the literature. Appendix Table A4 reports this statistic for the model for each group. It also reports the correlation between unemployment and vacancies, the Beveridge Curve, by group. When aggregated, the model economy generates a standard deviation for unemployment, relative to that of labor productivity, of 4.8. This is much larger than for Shimer's calibration (though less than half that for the data). There are three reasons for this. Most importantly, Shimer assumes a 40% replacement whereas the average of this rate across our four groups is much higher at 82%. Second, Shimer assumes a constant separation rate, whereas our model's separation rate is countercyclical and with a standard deviation comparable to that for the unemployment rate. Third, because volatility increases non-linearly with the replacement rate, the very high volatility for our low-wage, low-hours group is not offset by the low volatility of the high-wage, high-hours group. If we simulated our model economy with the same average replacement rate, but no heterogeneity, it would produce a standard deviation for (ln)unemployment that is lower by nearly a third. The model economy generates a Beveridge curve for the low-hours groups, but not for those with high hours. (The correlation between unemployment and vacancies equals -0.47 for low-wage, low-hours workers, but only -0.04 for the group with high wages and hours.) When aggregated, the model economy generates nearly as strong of a Beveridge Curve, correlation -0.44, as that just for those with low wages and hours. This reflects the disproportionate importance of the low-wage, low-hours workers in the unemployment pool. It also reflects the cyclical shift of the unemployed pool during recessions toward this group, which generates a lower vacancy rate.

[25] For the model a percentage point drop in employment reduces the average long-term hours worked of the

5. Conclusions

We have examined the ability of a DMP model of unemployment to explain cyclical fluctuations in both the employment and hours margins. Key to generating large fluctuations in the DMP model is the presence of sufficiently many workers who have little comparative advantage in the market (low rents to employment). Using the model, we map high market comparative advantage to working high hours conditional on being employed. This allows us to calibrate our model to the distribution of long-term wages and hours in panel data (the SIPP data).

The model correctly predicts higher separation and unemployment rates for workers with lower long-term wages and hours (lower comparative advantage). For business cycles the model predicts, correctly, that employment will be more cyclical for low-wage, low-hours workers. But the model fails to capture the cyclical magnitude of separations, especially for high-wage workers. Secondly, it fails to capture the capture the cyclical magnitude of the finding rate for high-hours workers. Together, these two failures cause it to considerably under predict the cyclicality of employment except for those with low comparative advantage in the market, that is, those with both low wages and hours.

unemployed by 0.5% purely from this compositional impact on the shares of the four groups in the unemployed pool. The finding rate is reduced by more than 1.5% for the same compositional reason–there are more low-hours workers among the unemployed. For the data we find that this same compositional effect reduces the average long-term hours of the unemployed by 0.2%, while also reducing the finding rate of the unemployed by 0.2%. Previous papers have argued that lower job-finding rates during recessions may reflect a compositional shift to unemployed workers who display lower job-finding rates. Darby, Haltiwanger, and Plant (1985) and Baker (1992) focus on the possibility of a shift in separations toward prime-age males during recessions. Pries (2008) considers the possibility that separations skew toward low-skilled workers in recessions. In these papers separations are treated as exogenous.

TABLE 1
Shares by group from SIPP data

	Wage Group	
Hours Group	Low wage	High wage
Low hours	26.7%	23.3%
High hours	23.3%	26.7%

TABLE 2
Deviation from Sample Means in Long-term Wages and Hours by Group
(***SIPP data***)

	Wage Group	
Hours Group	Low wage	high wage
Low hours	Wage: −37% Hours: −15%	+34% −10%
High hours	−30% +13%	+34% +12%

Based on sample of 73,416 men. Overall means are 2.70 for ln(wage) and 5.23 for ln(hours). Overall standard deviations are 0.42 for ln(wage) and 0.19 for ln(hours). Correlation between long-term wage and hours equals 0.15.

TABLE 3
Employment, separation, and finding rates by group
(***SIPP data***)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	Employment: 87.6% Separations: 2.36% Findings: 16.8%	95.0% 0.97% 15.5%
High hours	92.1% 1.89% 22.1%	96.8% 0.77% 21.3%

Overall means are 92.9% for employment (7.1% for non-employment rate), 1.45% for separation rate, and 18.5% for finding rate.

TABLE 4
Deviation from Overall Means in Long-term Wages and Hours by Group
(***Model simulations***)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	Wage: −34% Hours: −15%	+34% −15%
High hours	−36% +14%	+33% +14%

Overall standard deviations are 0.35 for ln(wage) and 0.15 for ln(hours). Correlation between long-term wage and hours equals 0.07.

TABLE 5
Employment, separation, and finding rates by group
(***Model simulations***)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	Employment: 83.8% Separations: 1.68% Findings: 8.8%	93.9% 1.04% 15.9%
High hours	95.5% 0.89% 18.8%	96.7% 0.75% 22.3%

Overall means are 92.3% for employment (7.7% for non-employment rate), 1.1% for separation rate, and 13.0% for finding rate.

TABLE 6
Relative business cycles in Employment by Group, Data compared to Model

	Wage Group			
Hours group	Low wage		High wage	
	SIPP data	Model	SIPP data	Model
Low hours	1.71 (0.09)	3.03 (0.09)	0.71 (0.12)	0.55 (0.06)
High hours	0.73 (0.07)	0.34 (0.03)	0.42 (0.06)	0.17 (0.01)

Coefficients are responses of (ln) employment rate to aggregated (ln) employment rate. For the SIPP data, the employment rate is instrumented based on U.S. average weekly hours and the unemployment rate for men. All monthly series are HP-filtered, with parameter of 900,000. SIPP data are seasonally adjusted. The SIPP data reflect 223 monthly observations per group. Standard errors (Newey-West corrected) are in parentheses. Statistics for the model are means across 100 simulations; standard deviations for the simulations are in parentheses.

TABLE 7
Business cycles in Hours and Employment by Group, Data compared to Model

		Wage Group			
Hours group		Low wage		High wage	
		SIPP data	Model	SIPP data	Model
Low hours	Hours:	0.46 (0.06)	0.63 (0.03)	0.26 (0.03)	0.70 (0.03)
	Employ-ment:	1.19 (0.09)	1.53 (0.12)	0.50 (0.07)	0.30 (0.02)
High hours		0.31 (0.08)	0.42 (0.02)	0.33 (0.05)	0.43 (0.01)
		0.48 (0.07)	0.19 (0.01)	0.28 (0.04)	0.09 (0.01)

Coefficients are responses of (ln) hours and (ln) employment rate to aggregated (ln) total hours (employment times hours). For the SIPP data, total hours are instrumented based on U.S. average weekly hours and the unemployment rate for men. All monthly series are HP-filtered, with parameter of 900,000. SIPP data are seasonally adjusted. The SIPP data reflect 223 monthly observations per group. Standard errors (Newey-West corrected) are in parentheses. Statistics for the model are means across 100 simulations; standard deviations for the simulations are in parentheses.

TABLE 8

Business cycles in Separation and Finding Rates, Data compared to Model

		Wage Group			
Hours group		Low wage		High wage	
		SIPP data	Model	SIPP data	Model
Low hours	Sep's:	−5.62 (1.69)	−4.40 (0.45)	−5.08 (1.85)	−1.96 (0.34)
	Find's:	2.41 (1.08)	7.88 (0.26)	2.55 (1.75)	3.03 (0.08)
High hours		0.28 (1.58)	−1.68 (0.23)	−2.22 (2.00)	−0.97 (0.19)
		5.35 (0.99)	2.26 (0.06)	3.43 (1.71)	1.68 (0.05)

Coefficients are responses of separation rate (in percentage points) and finding rate (in percentage points) to aggregate (ln) total hours (employment times hours). For the SIPP data, aggregate total hours are instrumented based on U.S. average weekly hours and the unemployment rate for men. All monthly series are HP-filtered, with parameter of 900,000. SIPP data are seasonally adjusted. The SIPP data reflect 223 monthly observations per group. Standard errors (Newey-West corrected) are in parentheses. Statistics for model are means across 100 simulations; standard deviations for the simulations are in parentheses.

TABLE 9

Aggregate Business cycles in Hours, and Employment, Data compared to Model

	SIPP data	Model
Hours	0.31 (0.03)	0.48 (0.03)
Employment	0.69 (0.03)	0.52 (0.03)

Coefficients are responses of aggregated (ln) hours and (ln) employment rate to aggregated (ln) total hours (employment times hours). For the SIPP data, total hours are instrumented based on U.S. average weekly hours and the unemployment rate for men. All monthly series are HP-filtered, with parameter of 900,000. SIPP data are seasonally adjusted. The SIPP data reflect 223 monthly observations per group. Standard errors (Newey-West corrected) are in parentheses. Statistics for model are means across 100 simulations; the standard deviations for the simulations are in parentheses.

TABLE 10

Aggregate Business cycles in Turnover, Data compared to Model

	SIPP data	Model
Separation rate	−3.02 (1.38)	−2.45 (0.24)
Finding rate	3.90 (0.80)	5.30 (0.12)

Coefficients are responses of (ln) separation rate and (ln) finding rate to the aggregated (ln) total hours. For the SIPP data, total hours are instrumented based on U.S. average weekly hours and the unemployment rate for men. All monthly series are HP-filtered, with parameter of 900,000. SIPP data are seasonally adjusted. The SIPP data reflect 223 monthly observations per group. Standard errors (Newey-West corrected) are in parentheses. Statistics for model are means across 100 simulations; the standard deviations for the simulations are in parentheses.

TABLE A1
Schooling by Wage and Hours Group (SIPP data)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	mean: 12.5 years 21.4% < 12 yrs 40.2% = 12 yrs 38.4% > 12 yrs	13.7 years 8.6% 35.1% 56.4%
High hours	12.7 years 17.4% 41.6% 41.0%	14.5 years 4.6% 25.6% 69.8%

Overall statistics: Mean 13.3 years, 13.9% <12 years, 35.9% =12 years, and 50.2% >12 years.

TABLE A2
Ages by Wage and Hours Group (SIPP data)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	mean: 37.2 years 31.4% are 20-29 51.3% are 30-50 17.3% are 51-60	41.2 years 13.3% 65.8% 21.0%
High hours	34.2 years 40.4 50.8 8.9	39.9 years 14.0 70.7 15.3

Overall statistics: Mean 38.1 years, 25.2% are 20-29, 58.9% are 30-50, 15.9% are 51-60.

TABLE A3
Fraction in Cyclical Industries by Wage and Hours Group (SIPP data)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	34.6%	43.5%
High hours	32.8%	42.2%

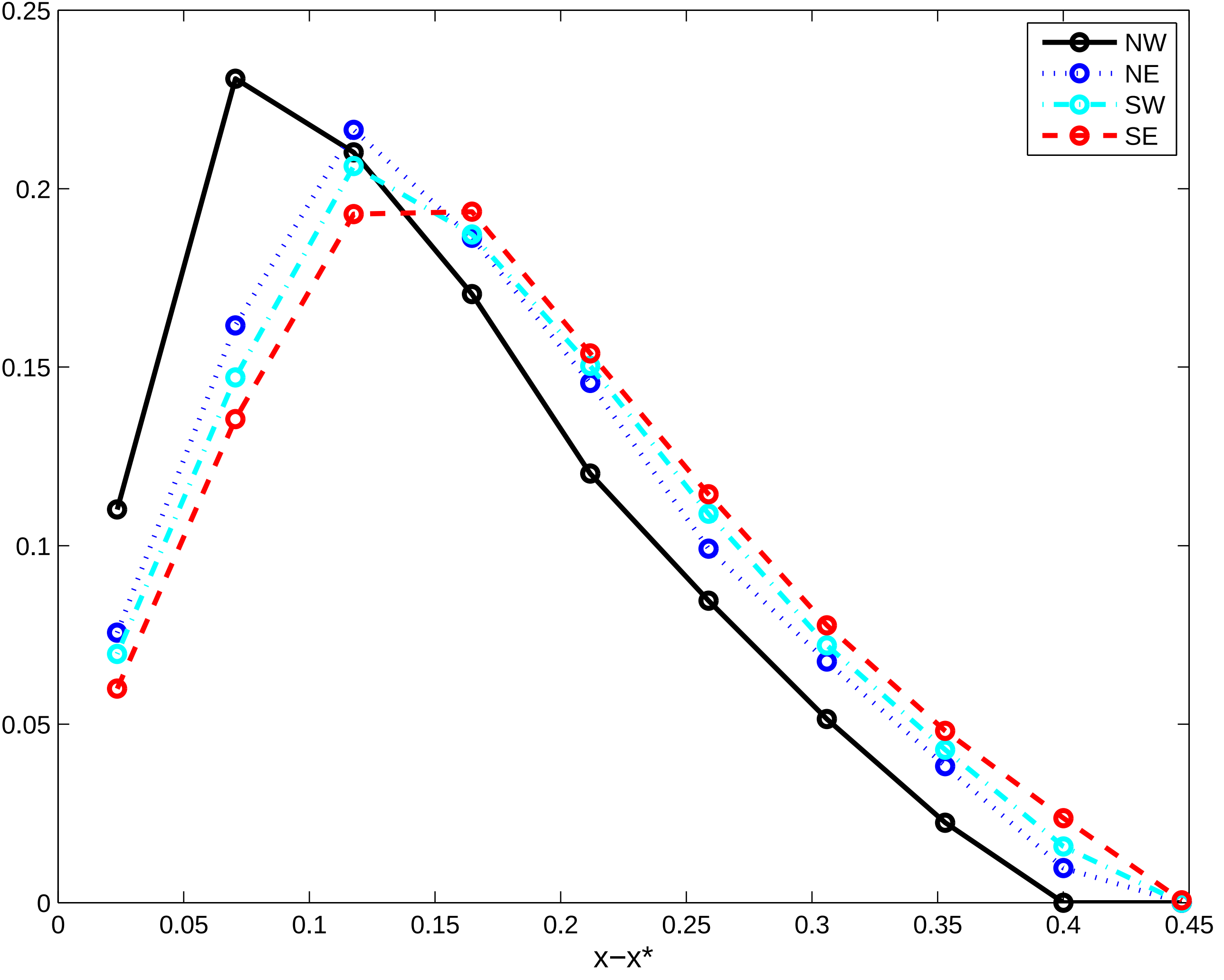
Industries classified as cyclical are construction, manufacturing and transportation. The overall fraction of workers in these industries is 38.3%.

TABLE A4
Cyclical Statistics for Model: Relative Standard Deviations for Ln(unemployment) and Ln(productivity), and correlation of Ln(unemployment) and Ln(vacancy rate)

		Wage Group	
Hours Group		Low wage	High wage
Low hours	σ_u/σ_z	6.35	3.47
	ρ_{uv}	−0.47	−0.33
High hours		3.05	2.19
		−0.05	−0.04

For the model economy aggregated σ_u/σ_z equals 4.81 and ρ_{uv} equals −0.44.

Figure 1: Distribution of Match Rents



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